Merging retrievals for passive microwave imagers and sounders

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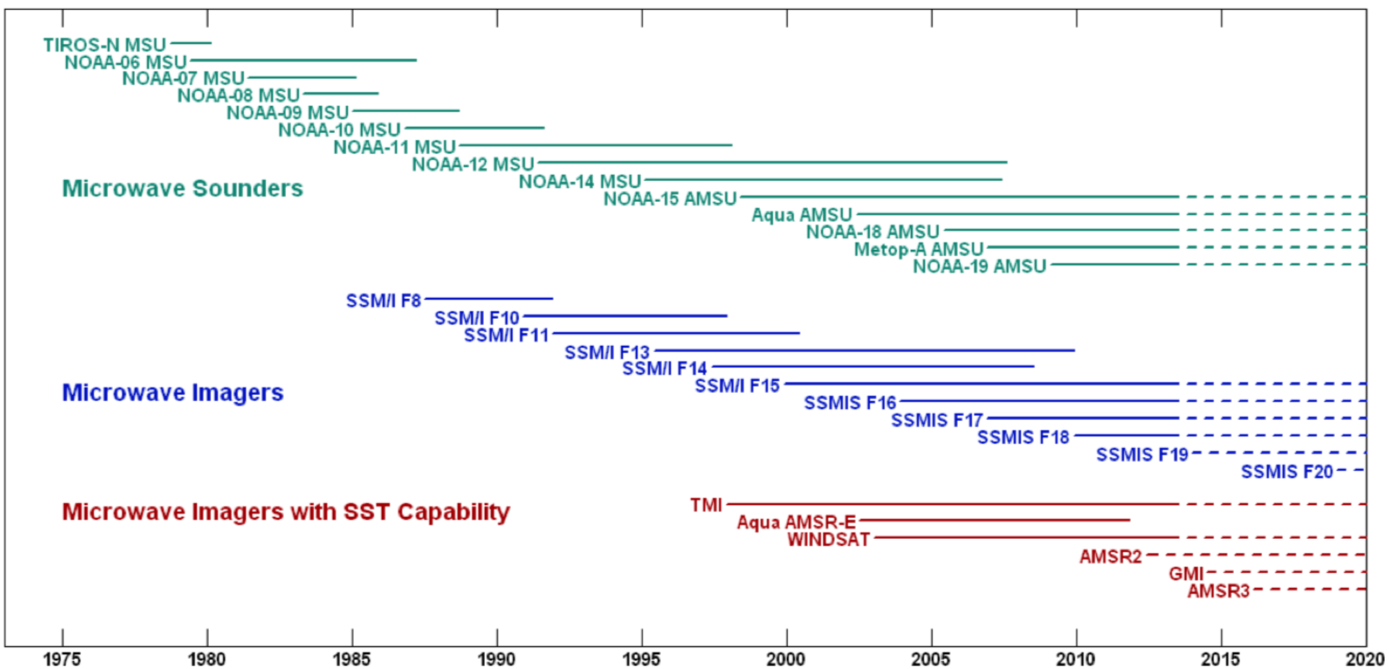
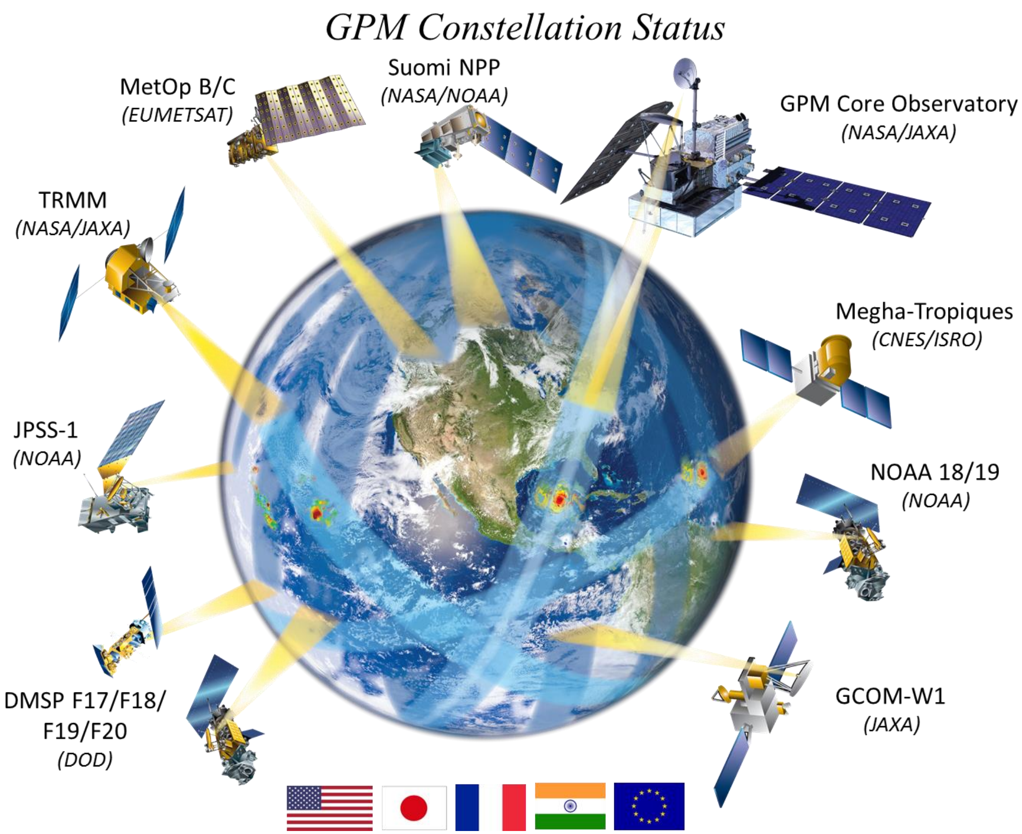
- Trend in passive microwave sensor capabilities towards more hyperspectral sensors, hybrids with imaging and sounding channels
- To take advantage, shift from separate algorithms for imagers and sounders to a more combined approach

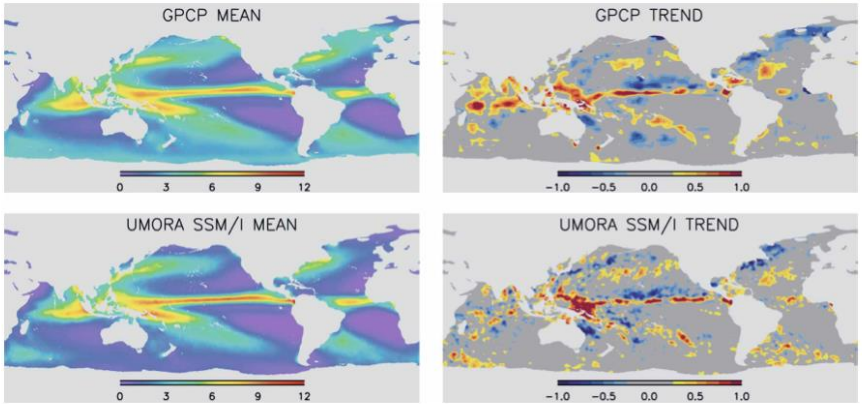


(Image from Frank Wentz)



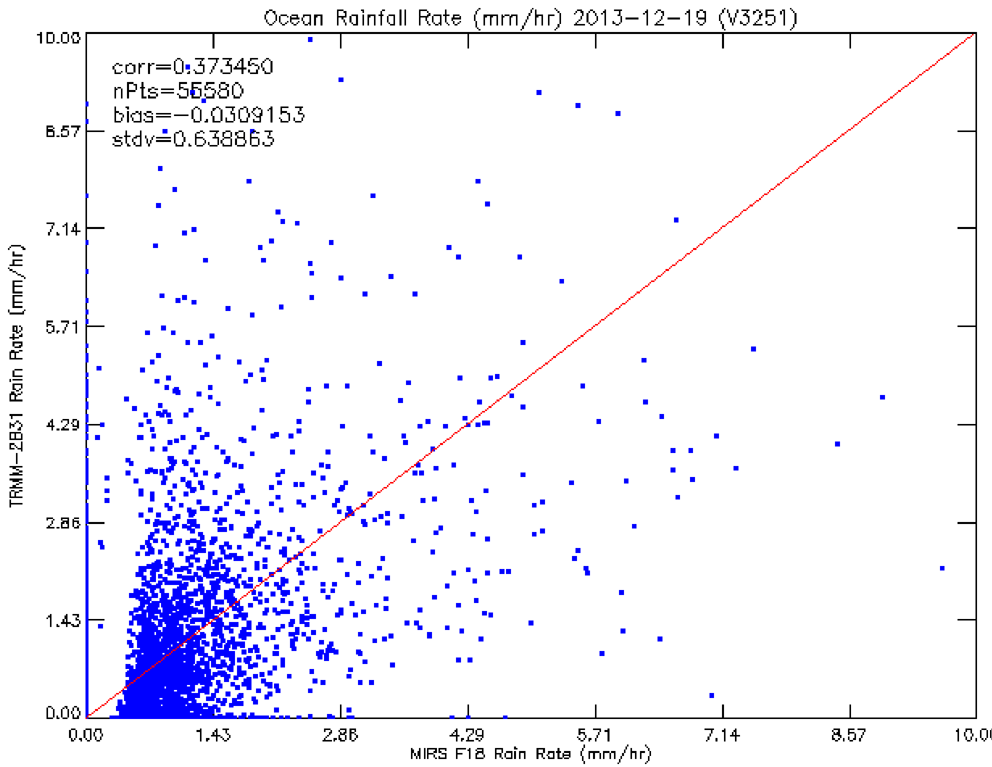
(Image from pmm.nasa.gov)

- The GPM constellation has a variety of sensor types
- Precipitation retrievals improve when given more information and constraints
- Uncertainty in global precipitation estimates closely tied to PMW retrievals



Hilburn and Wentz (2008)

The Idea: Use the strengths of two vetted microwave retrievals—GPROF and MiRS— to improve rainfall estimation in a way useful in the GPM era



- Mi nders (th
- GP GPM co
-
The Theo mathematics but applie

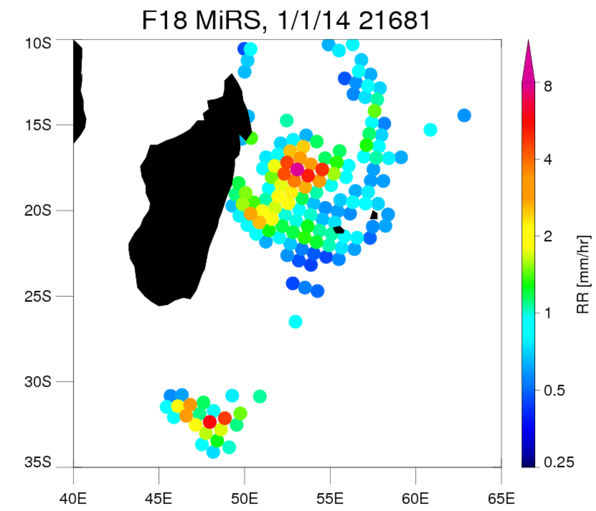
- Mi ariational) inv ieved, using NC
- GP from an *a priori* database stratified by environmental parameters
- Figure out how to leverage optimal estimation framework and the strengths of both algorithms to better constrain precip

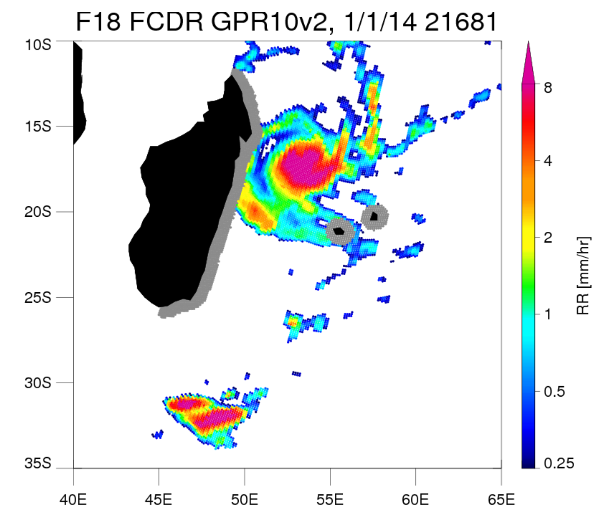
Comparison study using SSMIS F18

- Before modifications are made to the algorithms, a comprehensive comparison is done to provide a cont
- Focu re run for it op ounder char
- Com t impo are tied to rain
- A ca d for spec cident GPM

F18 SSMIS Sensor Characteristics (different from F16: first 5 channels are Horizontal)

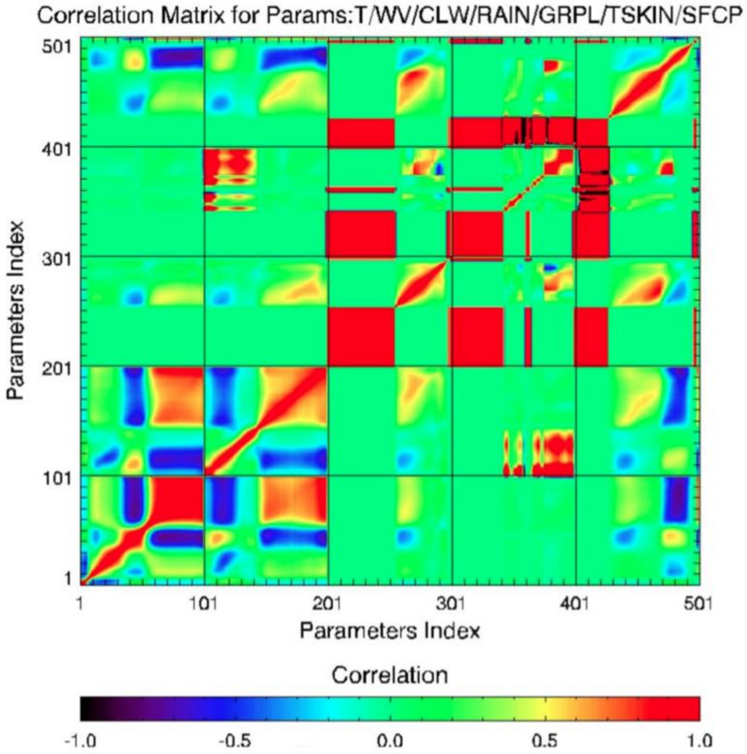
Channel	Center Freq.(Ghz)	Passband(Mhz)	Freq. (MHz)/Polar.	NEDT(Max) (K)	Sampling Interval(km)	Footprint(km)
1	50.3	400	10 H	0.4	37.5	38 x 38
2	52.8	400	10 H	0.4	37.5	38 x 38
3	53.596	400	10 H	0.4	37.5	38 x 38
4	54.4	400	10 H	0.4	37.5	38 x 38
5	55.5	400	10 H	0.4	37.5	38 x 38
6	57.29	350	10 RCP(*)	0.5	37.5	38 x 38
7	59.4	250	10 RCP	0.6	37.5	38 x 38
8	150	1500	200 H	0.88	37.5	14 x 13 (imager)
9	183.31±6.6	1500	200 H	1.2	37.5	14 x 13 (imager)
10	183.31±3	1000	200 H	1.0	37.5	14 x 13 (imager)
11	183.31±1	500	200 H	1.25	37.5	14 x 13 (imager)
12	19.35	400	75 H	0.7	25	73 x 47
13	19.35	400	75 V	0.7	25	73 x 47
14	22.235	400	75 V	0.7	25	73 x 47
15	37	1500	75 H	0.5	25	41 x 31
16	37	1500	75 V	0.5	25	41 x 31
17	91.655	3000	100 V	0.9	12.5	14 x 13 (imager)
18	91.655	3000	100 H	0.9	12.5	14 x 13 (imager)
19	63.283248±0.285271	3	0.08 RCP	2.4	75	75 x 75
20	60.792668±0.357892	3	0.08 RCP	2.4	75	75 x 75
21	60.792668±0.357892±0.002	6	0.08 RCP	1.8	75	75 x 75
22	60.792668±0.357892±0.006	12	0.12 RCP	1.0	75	75 x 75
23	60.792668±0.357892±0.016	32	0.34 RCP	0.6	75	75 x 75
24	60.792668±0.357892±0.050	120	0.84 RCP	0.7	37.5	75 x 75





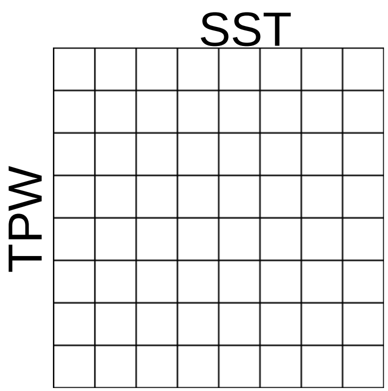
Modify the MiRS 1DVAR

- Hydrometeor profiles from the GPROF database can be used with MiRS covariance generation code, keeping other variables' covariances the same.
- With the goal of retrieving rain rates in the MiRS in mind, this should make MiRS and GPROF more consistent.
- This essentially assumes that the model-derived covariances and background states in the MiRS 1DVAR could be improved, as model biases will lead to retrieval biases.

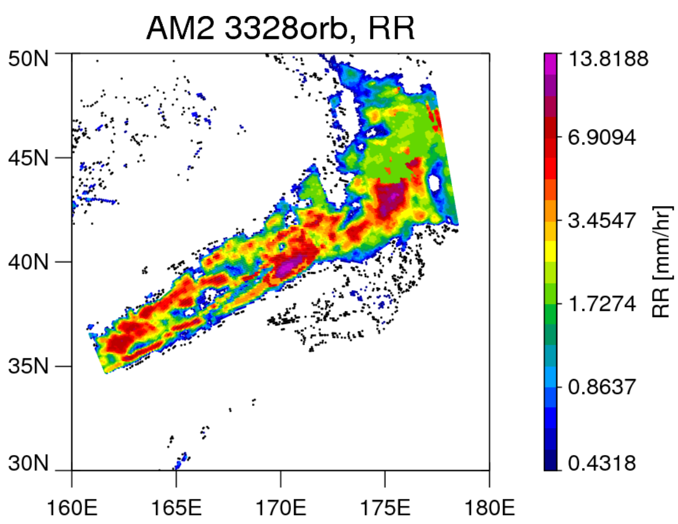


(Image from Boukabara et al. 2011)

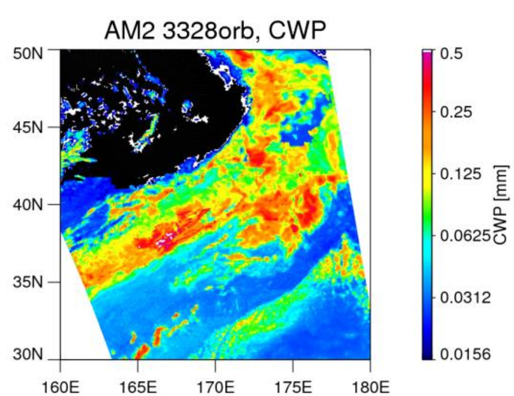
Towards retrieving rainfall in MiRS

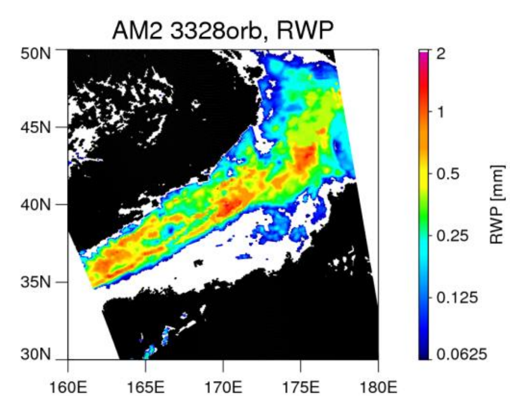


RR = 0.274 + 2.202*CLWP + 5.329*RWP – 0.302*IWP



- In contrast to the empirical rain rate calculation in MiRS, develop a physically-based approach to retrieve rainfall.
- Employ a dynamic LWP threshold for cloud/rain partitioning and use MiRS geophysical output as part of the Bayesian weighting in the GPROF database.
- The exact method employed will be flexibly determined, depending on earlier results.
- The method may not work for all sensors, depending on what channels are available.





Improve GPROF 2014 with MiRS

- Further constraining GPROF with environmental knowledge from the MiRS retrieval, could especially improve land and frozen precipitation retrievals
- For instance, stratify GPROF database by stability classifications derived from MiRS's profiles of temperature and moisture
- Since the AMSR2 ocean suite retrieval (developed at CSU) already uses an optimal estimation framework, leverage this alongside MiRS output t